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Cumulative Number of Deaths Predicting Model for Covid-19 Disease

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ABSTRACT

In this paper, we explain an explicit model function. Itestimate the total number of deaths in the Total population, and specifically, estimate the cumulative number of deaths in the India due to the current Covid-19 virus affect. Let's We compare the modeling results in to two related existing models along with a new criteria and several criteria for models election. The results show the proposed new model significantly suitably result better than the other two related models based on the India Covid-19 death data. We Findout that the errors of the fitted data and the predicted data points on the total number of deaths in the India from the last available data point and the next coming day are less than 0.4% and 1.5 %, respectively. The output show very related and predictability for the model. The new model shows that the maximum total number of deaths will be approximately 55308 across the India due to the Covid-19 virus, and with a 95% confidence that the expected total death toll will be between 53,432 and 57,249 deaths based on the data until 27 may, 2020. If any significant changes in the future days due to various testing strategies, social-distancing policies, there opening of community strategies, or a stay-home policy, the predicted death tolls will definitely change. Future work can be explored further to apply the proposed model to few many country Covid-19 death data and to other applications, the spread of disease, ect,

KEYWORDS: model prediction, model selection, Number of death estimation, model criteria, Covid-19

1. INTRODUCTION

Corona viruses that cause illness ranging from mild common cold, to more severe diseases, to severe illness and death. Recently Covid-19, known as Coronavirus disease 2019, has spread through people, first identified in Wuhan City, China, since December 2019.Covid-19 is a new disease, and even experts in the field are still learning how it spreads. It has rapidly spread to many countries around the world, including India.

The virus is spreading through people who are in close contact with one another by touching an infected surface or object and then touching their mouth or nose. Symptoms of infected persons withCovid-19 may include mild fever, cough, runny nose, sore throat, headache, shortness of breath, severe illness, or death.

According to the Medical council if India says, people can prevent the spread of viruses by staying home when they are sick, not touching their nose and mouth and covering their sneeze, and washing their hands more often with soap before eating or after touching objects from outside.

The out break of Covid-19 has rapidly spread countries around the world, including the India. As of 27 may 2020, more than 5,560 people in the India have died of coronavirus and there are at least 483,000 worldwide reported deaths, according to a tally by Johns Hopkins University

O n17 May, the World Health Organization (WHO) the projected that there would be 52,258 Covid-19 deaths with an estimated range between 44,063 and 120,381 deaths by 25 July, which is down from 55,308 as predicate dearlieron 19 May. Recently, Chinetal studied the stability and detection of severe respiratory syndrome corona virus in various environmental conditions including variables such as different temperatures and surfaces.

In this study, we are interested in developing a model that can estimate the cumulative number of deaths due to the ongoing Covid-19 virus pandemic occurring during the writing of this paper. Our preliminary analysis based on the Covid-19 global and India death data appears to be that the cumulative number of deaths seem to follow an S-shaped curve. There are a number of existing S-shaped logistic models in the literature and related logistic regression models. Pham recently developed a logistic model to estimate the number offailures.

In this paper, we modify the modeling reference by considering different unknown parameters that would allow flexibility to reflect the uncertainty of Covid-19 virus, such as different groups, age, and different environments and areas in the population. We compare the modeling results of the proposed model to two other slightly modified models as shown in Table1. We also discuss a new model selection criterion, called PC (Pham's criterion) and how to select the best model based on new criteria and several existing criteria, including SSE (sum of squared error), MSE (mean squared error), AIC (Akaike's information criterion), BIC (Bayesian information criterion), PIC (Pham's information criterion), PRR (the predictive ratio risk), and PP (the predictive power). With the new model, we illus rate the proposed model in estimating the cumulative number of deaths in the India.

Table 1: Models

Model	P(t)
Four-parameter logistic fault-detection model (Model 1)	$P(t) = \frac{a}{1 + d(\frac{1+\beta}{\beta+e^{bt}})}$
Modified model (Model 1)	$\mathrm{P(t)} = \mathrm{C} + \frac{a}{1 + d(\frac{1+\beta}{\beta+e^{bt}})}$
Five-parameter logistic model (New Model)	$P(t) = \frac{a}{1 + d(\frac{1+c}{\beta+e^{bt}})}$

Section 2, discusses a closed-form new model function to estimate the total number of deaths in the population and also briefly discusses a new criterion for model selection and some existing criteria. Section 3, discusses the modeling results based on the Covid-19 death data in the India. Section 4, briefly discusses the findings and makes some concluding remarks.

2. MODEL DEVELOPMENT ON ESTIMATING THE NUMBER OFDEATHS

In this study, we develop a model that can estimate the cumulative number of deaths in the population. We use the proposed model to estimate the cumulative number of deaths due to Covid-19, the current deadly virus. In this section, we first present the model assumptions and the results of the proposed model.

2.1. *ModelConsiderations*

In this study, we assume that

1. There are a few people in the population who have already been infected with Covid-19, and are spreading the virus into the community but do not know that they are infected with the virus. The virus is spreading through people who are in close contact with one another. An infected person may, for example, cough or sneeze, spreading the virus through the bacteria eventually coming in contact with the mouths or noses of other people who are nearby or possibly directly in haled into their lungs. A person can get Covid-19 by touching an infected surface or object and then touching their own mouth, nose, or possibly their eyes.
2. The virus is spreading through out the areas based on a time-dependent infection rate perpers on in which it will spread data very slow rate from the beginning due to a small number of infected people and will spread data growth rate much faster due to a higher number of people who have already been infected with the virus and who are in close contact with non-infected individuals as time progresses. The growth rate will then continue to grows lowly until it reaches the maximum total number of Covid-19 deaths.
3. The rate of change of the death is the derivative of the number of deaths $P(t)$ is directly proportional to both the number of deaths $p(t)$ who have infected the virus and the number of people in the susceptible population who have not yet been infected, based on the time-dependent rate infections per person per unittime.
4. Deaths are proportional to infections, but with a lag. There can be a significant time lag between when someone is infected and when they die. We assume that death data is more reliable than there ported number of cases and hospitalizations due to the uncertainty of testing mechanisms and the recognized symptoms and treatments. Additionally, it is easier to determine cause of death than cause of hospitalization sand test cases. Infect, we need to know how tests are being conducted; otherwise, there will be a lot of uncertainty about the number of Covid-19 cases, so they will not be very usefulindicators.

2.2 Model Development

Let P(t) denote the cumulative number of deaths at time t, $b(t)$ denote the time-dependent death rate per person per unit time, and a denote the maximum total number of deaths. Numerous researchers in the past several decades have studied the areas of population growth and disease spread, and several well-known population growth models, including logistic model in the literature

$$\frac{\mathrm{dp(t)}}{dt} = b(t)p(t)(a - p(t))$$

Given a vast literature in this area we can write the differential equation (with the initial condition m(0) Ç=0 in this case) governing death rate growth as follows

$$P(t) = \frac{a}{1 + d(\frac{1+c}{\beta+e^{bt}})}$$

Based on the model considerations above and the generalized death rate change differential function as given in First equation, In this paper we propose the following model to estimate the cumulative number of deathwhere *a*, *b*, *c*, *d*, and β are the unknown constant parameters.

As from assumption 1, there are a few people in the population who have already been infected with Covid-19 at the beginning at time $t = 0$. From Second equation, it is easy to realize that the initial value of the function $P(t)$

$$P(0) = \frac{a}{1 + d(\frac{1+c}{\beta+1})}$$

At$t\to\infty$,$p(\infty)=a$. This indicates that the maximum total number of deaths in the population is *a*, where *a* can be estimated based on givendata.

We estimate these unknown parameters *a*,*b*,*c*,*d*, and β by using the least squares estimate method and compare their results based on various model criteria. In general, adding more parameters in the model improves the goodness of the fit. Some existing model selection criteria have taken into account the penalty imposed by adding more parameters to the model. The two common criteria are AIC and BIC. For example, BIC has taken in to account the sample size that show strongly it impacts the penalty by adding the number of parameters in the model, while AIC does not depend on the sample size.

In the next section, we present a new criterion for model selection that takes into account the uncertainty in the model and the number of parameters in the model by slowly increasing the penalty when adding parameters in the model each time where the sample is too small compared to the sample size.

3. MODELING ANALYSIS AND PREDICTION RESULTS

In this section, we use the model given in Second equation to calculate the total number of deaths based on the death data in the India consisting of 88 days obtained from World meter for a period beginning from 1 March 2020 to 27 May 2020.

We compare the modeling results of the new model to two slightly related models as shown in Table 1 and select a best model based on a proposed new criteria PC and several existing criteria such as SSE, MSE, AIC, BIC, PIC, PRR, and PP. Table 2 provides a brief definition of those criteria to be used in selecting the best model from among the models in Table 1. For all these criteria, the smaller the value, the better the model fits.

The cumulative number of deaths data in the United States is shown in Table 3. We use the least square estimate (LSE) method to estimate the model parameters using R software. We also compare the results of the models listed in Table 1.We then discuss the best model among the models in Table 1 based on various model selection criteria. Table 4 summarizes the results of the parameter estimates of all three models from Table 1 using LSE. Table 5 shows the calculation results and the rank of each model based on the modeling criteria as given in Table 2.

Table 2: Model selection criteria

No	Criteria	formula	
1	SSE	$\sum_{i=1}^{n}(yi - \hat{y}i)^2$	Measures the total deviations between the predicted values with the actual data observation
2	MSE	$\frac{\sum_{i=1}^{n}(yi - \hat{y}i)^2}{n-k}$	Measures the difference between the estimated values and the actual observation
3	AIC	$-2\log(L) + 2k$	Takes into account the penalty term by adding more parameters.
4	BIC	$-2\log(L) + k\log n$	Takes into account the penalty based on the sample size and the number of parameters in the model.
5	PIC	$SSE + k(\frac{n-1}{n-k})$	Takes into account more penalty when adding too many parameters in the model
6	PRR	$\sum_{i-1}^{n}(\frac{\hat{m}(t) - yi}{\hat{m}(ti)})^2$	Measures the distance of model estimates from the actual data against the model estimate.
7	PP	$\sum_{i-1}^{n}(\frac{\hat{m}(t) - yi}{yi})^2$	Measures the distance of model estimates from the actual data against the actual data
8	PC (Pham's criterion)	$(\frac{n-k}{2})\log(\frac{SSE}{n}) + k(\frac{n-1}{n-k})$	Takes into account the tradeoff between the uncertainty in the model and the number parameters

As we can observe from Table 5, the new model has the smallest values and their corresponding rankings are first according to criteria such as SSE, MSE, AIC, PIC, and PC (new criteria) but not BIC, PP, and PRR criteria. We observe that the results of proposed PC agree with MSE and AIC criteria but not BIC. It is worth noting that the new PC takes into account the uncertainty in the model and the dynamic penalty depending on both the same size and the number of parameters in the model where the penalty term in BIC for the number of parameter sin the model heavily depend on the same size. The plot sin Figures 1-4, show the estimated cumulative number of deaths versus the actual death data in the India during the period of 1 March 2020 to 27 may 2020. The results indicate the proposed model is the best fit to estimate the cumulative number of deaths for the India Covid-19data.

The new model as shown in Figure 3 and Table 5 indicates that it provides the best fit based on SSE, MSE, AIC, PIC, and PC. The proposed model fits significantly better than the other related models as shown in Table 6 for the India Covid-19 death data.

Table 3: India deaths data during 1/03/20—27/5/20

Date	Death	Date	Death
01/03	1	29/05	938
02/03	4	30/05	1009
03/03	6	01/05	1092
04/03	7	02/05	1175
05/03	13	03/05	1369
06/03	16	04/05	1480
07/03	24	05/05	1569
08/03	29	06/05	1672
09/03	32	07/05	1767
10/03	38	08/05	1895
09/04	83	09/05	1998
10/04	119	10/05	2085
11/04	151	11/05	2207
12/04	190	12/05	2341
13/044	218	13/05	2441
14/04	250	14/05	2544
15/04	286	15/05	2664
17/04	317	16/05	2821
18/04	357	17/05	2955
19/04	401	18/05	3095
20/04	450	19/05	3295
21/04	484	20/05	3695
22/04	521	21/05	3725
23/04	577	22/05	3812
24/04	624	23/05	3969
25/04	684	24/05	4320
26/04	735	25/05	4512
27/04	794	26/05	5001
28/04	861	27/05	5560

Table 4: Parameter estimates using least squares method

Model	P(t)	Parameter Estimates
Model 1	$P(t) = \frac{a}{1+d(\frac{1+\beta}{\beta+e^{bt}})}$	a = 4900 , b = 0.1774159 d = 400.013, β = 2.977112
Model 2	$P(t) = C + \frac{a}{1+d(\frac{1+\beta}{\beta+e^{bt}})}$	a = 4400, b = 0.177 c = 0.49804, d = 42.0186 β= 3.32222
Model 3	$P(t) = \frac{a}{1+d(\frac{1+c}{\beta+e^{bt}})}$	a = 5500, b = 0.1535604 c = 1.6586221, d = 38.99688 β=-6.9747477

Table 5: Modeling results and rankings based on various criteria

Criteria	Model 1 (Rank)	Model 2 (Rank)	New Model (Rank)
SSE	16,888,788 (2)	17,383,120 (3)	16,165,633 (1)
MSE	337,775.8 (2)	354,757.5 (3)	329,910.9 (1)
AIC	691.2715 (2)	694.8294 (3)	690.9084 (1)
BIC	699.2275 (1)	704.7743 (3)	700.8533 (2)
PIC	16,888,792 (2)	17,383,125 (3)	16,165,638 (1)
PRR	17.66833 (1)	17.94312 (2)	54.3795 (3)
PP	42,211.26 (1)	57,031.17 (2)	605,026.3 (3)
PC	320.5694 (3)	316.1178 (2)	314.3388 (1)

Table 6: Prediction results

Estimation	Real Observation	Model 1	Model 2	New Model
Fitted Value	5100	5301	5467	5501
Predicted value	4358	5573	4371	5568

We observe that the errors of the fitted and predicted data points on the death toll in the India on the last available data point and the next coming day are less than 0.4% and 1.5%, respectively. Our model fits significantly well based on the India death data. The results show very encouraging predictability for the model. The new model predicts that the maximum total number of deaths will be approximately 55, 308 across the India due to the Covid-19 virus, with a 95% confidence that the expected total death toll will be between 54, 951 and 56, 249 deaths based on the data until 27 May 2020. If there is a significant change in the coming days due to various testing strategies, social-distancing policies, reopening the community, or stay-home policy, the predicted death tolls will definitely change. Obviously, further analysis in broader validation of this conclusion is needed by updating the real current Covid-19 data into the model.

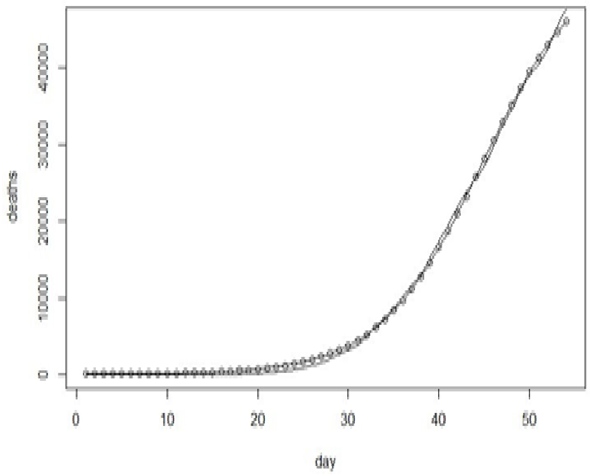

Figure 1: The estimated cumulative number of deaths vs actual death data from Model 1

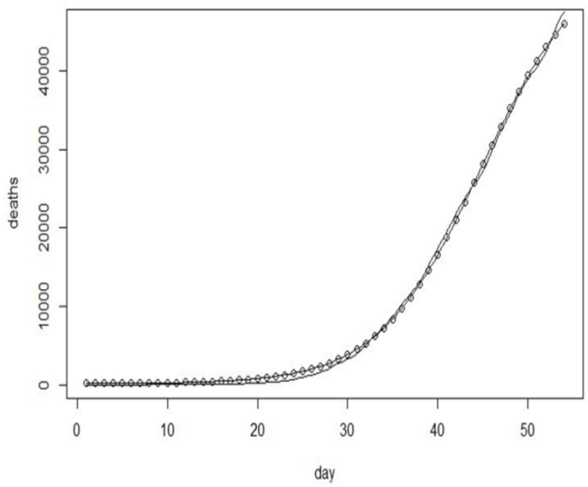

Figure 2: The estimated cumulative number of deaths vs actual death data from Model 2

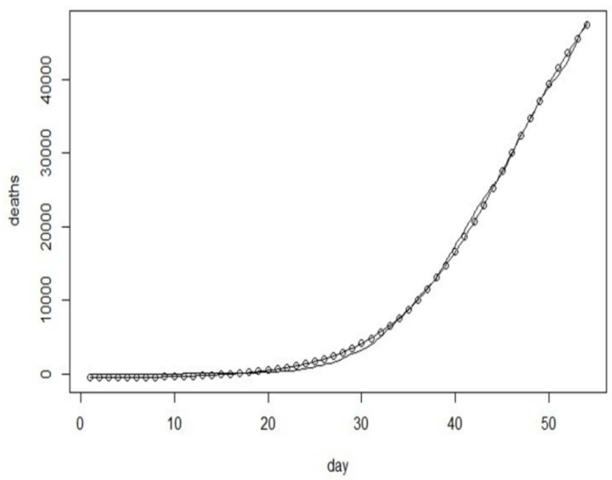

Figure 3: The estimated cumulative number of deaths vs actual death data from Model 3

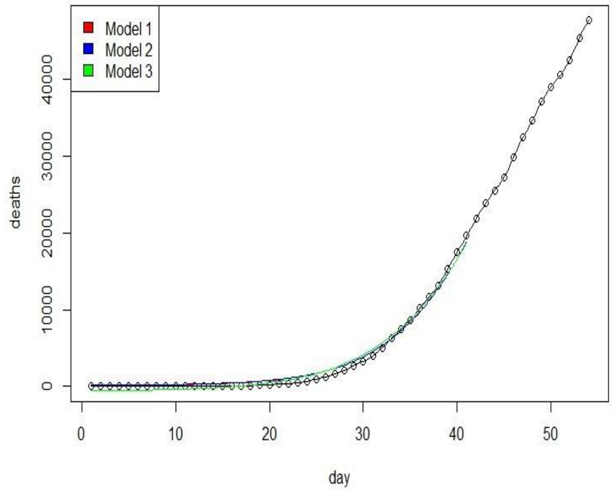

Figure 4: The estimated cumulative number of deaths vs actual death data from all three models

4. CONCLUSIONS

In this paper, an explicit model function to predict the total number of deaths in the Infected population is presented. We also discuss a new criterion that can choose the best model in the set of candidates. There results of the model parameter estimates of the proposed model and two related proposed models using the least squares method for the Covid-19 death data in the India. are presented. The proposed model fits significantly better than two other related models based on the Covid-19 death data in the India. The results show very encouraging predictability for the model.

Further work can be done to apply the proposed model to Covid-19 global death data as well as any other countries such as Brazil and Russia where they l so have a large cumulative number of deaths due to Covid-19. In the future, we intend to use the model in applications of population mortality, the spread of disease, etc.

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